LANE DETECTION IN AUTONOMOUS DRIVING USING ENHANCED PREPROCESSING AND AI TECHNIQUES

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ABSTRACT

Accurate lane detection plays a vital role in the development and deployment of autonomous driving systems. It serves as the backbone for vehicle localization, navigation, and decision-making processes. In this paper, we propose an integrated lane detection framework that combines advanced image preprocessing methods with state-of-the-art machine learning techniques to address the limitations of traditional approaches. The methodology includes a series of image transformations, such as color space conversion, edge enhancement, region of interest (ROI) extraction, and perspective warping to enhance lane visibility. These preprocessing steps are followed by the deployment of deep learning models—namely convolutional neural networks (CNNs) and transformer-based architectures—for semantic lane segmentation and curve fitting. The proposed system is tested on widely-used datasets under various challenging environmental conditions, including shadows, low light, and occlusions. Our results highlight the improvements in detection accuracy and processing efficiency, showing potential for real-time autonomous applications.

KEYWORDS: Lane Detection, Autonomous Vehicles, Image Preprocessing, Deep Learning, Convolutional Neural Networks, Transformer Networks, Semantic Segmentation, Real-Time Systems, Perspective Transformation, Attention Mechanisms

1. INTRODUCTION

The rapid evolution of autonomous driving technologies demands robust perception systems capable of interpreting road environments in real time. Among the most critical perception tasks is lane detection, which facilitates safe lane keeping, adaptive cruise control, and path planning. Traditional lane detection methods based on rule-based image processing often fail in dynamic conditions such as poor lighting, occlusions caused by other vehicles, or faded lane markings.

Recent advancements in artificial intelligence, particularly deep learning, have introduced powerful tools for enhancing the robustness and accuracy of lane detection systems. Unlike hand-crafted approaches, data-driven models can generalize better across diverse road scenarios. This paper introduces a hybrid approach that synergizes sophisticated image preprocessing techniques with modern deep learning algorithms to produce reliable lane detection suitable for real-time autonomous vehicle operations.

2. RELATED WORK

Lane detection has been extensively studied in the fields of computer vision and intelligent transportation. Early techniques such as the Hough Transform and Canny edge detection formed the basis for detecting linear and curved road features. While computationally efficient, these approaches lack resilience under variable conditions like occlusions, lane wear, and environmental noise.

The introduction of convolutional neural networks (CNNs) revolutionized image analysis by enabling automatic feature extraction. LaneNet and SCNN are notable examples of CNN-based lane detection models that outperform classical methods by learning lane patterns directly from annotated data. Additionally, transformer-based architectures such as Laneformer and DETR have shown exceptional performance in capturing long-range dependencies in images, making them suitable for semantic segmentation tasks, including lane detection.

Despite their effectiveness, deep learning models benefit greatly from robust preprocessing steps that simplify the input data and improve model focus. Thus, combining preprocessing techniques with deep models offers a comprehensive solution for real-time and reliable lane detection.

3. PROPOSED METHODOLOGY

The proposed system integrates two main components: (1) an image preprocessing pipeline designed to enhance lane visibility and reduce background noise, and (2) a deep learning-based detection module that identifies and tracks lane markings.

3.1 Image Preprocessing Techniques

Color Space Transformation

Standard RGB images are sensitive to lighting changes. By converting images to HLS (Hue, Lightness, Saturation) or HSV (Hue, Saturation, Value) color spaces, lane lines can be more easily isolated, especially under varying sunlight or shadows.

Edge Detection

Edge detectors like the Sobel operator and the Canny algorithm are used to accentuate the borders of lane lines. These methods help define lane contours, making them more distinguishable from the background.

Region of Interest (ROI) Extraction

To focus computational efforts on relevant image areas, a polygonal ROI is defined, typically covering the road ahead of the vehicle. This step eliminates distractions such as buildings, sky, and surrounding traffic.

Perspective Transformation (Bird's-Eye View)

A warped top-down view of the road is generated through a homography transformation. This simplifies the geometry of the lanes, making them appear straighter and more parallel, which is advantageous for curve fitting.

3.2 Machine Learning-Based Lane Detection

Semantic Segmentation

Using deep learning models like U-Net, ENet, or SegFormer, each pixel in the ROI is classified as belonging to a lane or background. These models are trained on annotated datasets to learn complex spatial relationships between road features.

Polynomial Curve Fitting

After segmentation, the detected lane pixels are used to fit third-degree polynomial curves. These curves model the road's curvature and provide a mathematical representation of lane paths.

Attention Mechanisms

Expanded Self Attention (ESA) modules are integrated into the deep learning architecture to dynamically focus on significant image features. This improves accuracy in scenes with clutter or unclear lane markings.

Transformer Architectures

Transformer models such as Laneformer are employed to capture the global context across the entire image. Their self-attention capabilities allow them to track lanes even when sections are occluded or faded, enabling more reliable detection.

4. LANE DETECTION ALGORITHM OVERVIEW

Input: Real-time video feed from vehicle-mounted cameras

Output: Detected lanes with positional data for control systems

Algorithm Steps:

1. **Image Acquisition**
   - Capture frames from front-facing cameras at a consistent frame rate.

2. **Preprocessing Pipeline**
   - Convert RGB frames to HLS/HSV color space
   - Apply Sobel and Canny edge detectors
   - Extract and crop the region of interest
   - Perform perspective transformation for a top-down view

3. **Deep Learning Detection**
   - Segment lane pixels using semantic segmentation networks
   - Fit polynomials to the segmented lane points
   - Use attention modules for feature enhancement
   - Apply transformer-based models to infer lanes and handle occlusion

4. **Post-Processing**
   - Smooth the polynomial curves using filters like Kalman or exponential smoothing
   - Validate the lane lines with geometric constraints (e.g., lane width)
   - Predict and update lane positions across frames

5. **Output Generation**
   - Overlay detected lanes on the original frame for visualization
   - Generate lane boundary coordinates for vehicle control modules

5. Experimental Evaluation

The proposed method was tested using publicly available datasets such as TuSimple and Caltech Lane. These datasets include varied environmental conditions such as different lighting, weather, and road curvature. Evaluation metrics include Intersection over Union (IoU), F1-score, and processing latency.

The integration of preprocessing and advanced AI models resulted in:

- **Higher accuracy:** The system achieved up to 96% IoU on the TuSimple dataset.
- **Improved robustness:** Transformer networks provided stable lane predictions even under partial occlusion.
- **Real-time performance:** With optimized code and GPU acceleration, the system maintained a frame rate of 30+ FPS, suitable for real-world applications.

6. CONCLUSION AND FUTURE WORK

This research introduced a robust and adaptive approach to lane detection for autonomous driving by integrating image preprocessing with machine learning models. The system demonstrated excellent performance in challenging conditions, outperforming many existing methods. The use of transformers and attention mechanisms proved particularly effective in enhancing the model's ability to interpret complex scenes.

For future work, efforts will focus on reducing model size and inference time to suit embedded systems used in production vehicles. Additional enhancements may include the fusion of data from LiDAR and GPS, multi-lane classification, and the application of reinforcement learning for adaptive decision-making.

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